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MOBILITY AND INNOVATION IN AN R & D ORGANIZATION

David G. Anderson

November 1984

SSM WP# 1609-84

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Note: This research was sponsored by McKinsey & Company, Inc. All findings and opinions expressed herein are those of the author alone, who is solely responsible for their content.
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ABSTRACT

The effects of two career variables (time in job and career breadth) on individual innovation were tested on a sample of 264 scientists and engineers in an industrial research and development laboratory in the context of a theory of individual-level innovation. Results of testing the structural equation model revealed that time in job and breadth of project and functional experience may have weak positive effects on innovation. LISREL measurement modeling (confirmatory factor analysis) was used to validate and refine the variable measures used in the study. This approach to "triangulating" variables revealed several instances where multiple measures hypothesized to reflect a single underlying factor (including some scales used extensively in the literature) failed to achieve acceptable tests of convergent validity.

The effects of a number of other variables on innovation were also tested. Several personal style and attitude variables had significant effects on innovation, while the effects of most job characteristic variables examined were not significant. One variable that had a significant positive effect on innovation, for example, measured an individual's tendency to move back and forth between abstract principles and concrete situations. These and other findings suggest that it may be time to "bring the individual back" into studies of the innovation process by assessing the impact individual difference variables have on organizational innovation.

JOB MOBILITY AND INNOVATION IN AN R&D ORGANIZATION

Patterns of intraorganizational job mobility -- the movement of individuals through different jobs or assignments within an organization -- vary significantly across different organizations. Differences in size, growth rate, management philosophy, and other factors influence the kind of mobility pattern an organization exhibits.

One key variable related to intraorganizational mobility patterns is the average time employees spend in their jobs (or its reciprocal, the job mobility rate -- the average rate at which employees change jobs). A job attitude survey administered recently to employees at two different companies -- a medium-sized manufacturer of industrial specialty products and a small construction engineering firm -- showed that the average time in job for employees differed substantially between them. Among the questions asked on both surveys was, "How long have you been in your present job?" This question listed several ordered categories for respondents to check (e.g., "less than 6 months," "6 months to 1 year"...."more than 5 years").

Assuming that job changes are distributed as Poisson random variables, simple curve-fitting showed that employees remain 26 months in their jobs, on average, at the manufacturing company, compared with 36 months -- almost 40% longer -- at the construction engineering firm. Excluding new hires from the data widened the difference between the two companies' average time in job to 32 months, or almost 3 years. Average time in job varied across

different functions in both companies, too -- from 1 1/2 to 3 years in the manufacturing company and from 2 to nearly 5 years in the construction company.[1]

Another intraorganizational mobility variable that can vary across organizations is the "breadth" of typical career paths -- the diversity of work that employees typically experience during their careers. Some companies emphasize developing broad exposure to many parts of their business in management development and career counseling programs, while others stress building expertise in narrowly defined functional specialties. Among many of IBM employees, for example, "IBM" has come to stand for "I've Been Moved," because the company moves them around to new assignments so often. Other companies in the computer industry (e.g., Control Data, Honeywell, Hewlett-Packard, Digital) do not appear to stress broad job mobility as much as IBM. Such differences in philosophy are probably reflected in different patterns of cross-functional and geographical mobility.

Most research on intraorganizational mobility has concentrated on understanding its causes. Labor economists have examined the effects of external labor markets on "internal labor markets" (Doeringer and Piore, 1971). Demographers have used stable population theory to explore the effects of organizational growth and decline, work force aging, and other social processes on mobility patterns (Keyfitz, 1973; 1977; 1980; Pfeffer, 1979). Sociologists have examined the effects of grade-level ratios and hiring policies on mobility patterns using vacancy chain models (Stewman, 1979; Konda and Stewman, 1980; Stewman and Konda, 1981).

Other researchers have debated the applicability of various mobility models (e.g., Markov models, semi-Markov models, social matching models, tournament models) for describing how individual careers unfold within organizations (Blumen, Kogan, and McCarthy, 1955; Tuma, 1976; March and March, 1977; 1978; Rosenbaum, 1979).

Research on the effects of different mobility patterns has focused mostly on flows of people across organizational boundaries (interorganizational mobility) rather than flows of people within organizations. The effect of leader succession on organizational performance, for example, is one topic that continues to stimulate research (Grusky, 1963; 1966; Allen, Panian, and Lotz, 1979; Carroll, 1984). Several organizational theorists have mentioned intraorganizational mobility as a source of integration needed to balance professionalization and specialization (Thompson, 1965; 1969; Lawrence and Lorsch, 1967). Other researchers have studied mobility between widespread geographical divisions as a mechanism of organizational control (Edstrom and Galbraith, 1977; Ouchi and Johnson, 1978; Foy, 1980). By and large, however, the effects of intraorganizational mobility are not well understood. As a result, organizational researchers have provided little guidance to companies regarding how different employee development policies might affect their organization and their employees (Super and Hall, 1978).

BACKGROUND AND THEORY

The research reported here examines the effects of two

mobility variables -- time in job (or job tenure) and career breadth (the diversity of a person's career history) -- on the innovation of individual scientists and engineers in an industrial research and development laboratory. While the effects of these variables are tested at the individual level, some straightforward assumptions allow inferences to be made about how different organizational mobility patterns might affect organizational innovation.

At the organization level, the effects of job mobility on innovation have been discussed in the literature for many years. Burns and Stalker (1962) identified fluid movement of people among jobs as one characteristic of organic, innovative organizations. Researchers studying large Japanese business organizations have noted the unusual amount of cross-training, job rotation, and role flexibility which characterizes many of them (Rohlen, 1974; Vogel, 1975; Cole, 1979; Pascale and Athos, 1981). Ouchi and his colleagues have identified nonspecialized career paths as a central characteristic of Japanese-like "Type Z" organizations (Ouchi and Johnson, 1978; Ouchi and Jaeger, 1978; Ouchi and Price, 1980). Thompson (1965), Bennis (1966), and Toffler (1970) describe innovative organizations as full of temporary "ad hoc" structures (project teams, task forces, etc.) whose missions and membership are changing constantly. Even the organizational ecology literature contains occasional references to job changes as one source of variation or "foolishness" in organizations (March, 1973; Weick, 1979; Aldrich, 1979).

The thrust of all these ideas is that the more employees move

around, the more innovative an organization will be. On the other hand, this notion runs counter to a fundamental tenet of sociology and economics -- that specialization and the division of labor produce economies which result in greater efficiency and productivity (Durkheim, 1933; Becker, 1964; Doeringer and Piore, 1971). Mobility can impose substantial costs on organizations, and in the "real world" of work most companies resist moving their employees around willy-nilly. It may be that these companies aren't interested in stimulating innovation. More likely, they see some significant tradeoffs between increased job mobility and innovation, efficiency, and productivity in their operations.

One source of theories linking mobility and innovation suggests that there is a middle ground - an optimal degree of mobility. Since 1956, four independent studies have confirmed that the productivity of project teams first rises and then falls as the average tenure of project team members increases (Shepard, 1956; Wells, 1962; Smith, 1979; Katz, 1982). All four studies found that maximum productivity occurred when project-team members' tenure averaged between 2 and 4 years.[2]

In this study, two principal hypotheses relating mobility and innovation were tested on a sample of 264 scientists and engineers working at a large industrial R&D lab, using a cross-sectional structural equation model of individual innovation in the lab. A brief description of this model is given below. The general theory of individual innovation from which the equations were derived and the model's specific hypotheses are described in detail elsewhere (Anderson, 1984). The origins of the theory are a series of

models discussed in Anderson (1981).

Based partly on a theory of innovation developed by Mohr (1969), innovation is hypothesized to be affected by three broad groups of variables -- information variables, motivation variables, and resource variables. Each of these three groups contains three variables, all which are listed and defined briefly in Table 1.

Insert Table 1 about here

Each of the nine primary causal variables (called "primary" because they are hypothesized to affect innovation directly) has its own causal model. The variables which are hypothesized to affect these primary variables are called "exogenous variables;" they are listed in Table 2.

Insert Table 2 about here

The complete model of individual innovation contains 25 variables linked together in a system of ten simultaneous equations. These equations are shown in Figure 1.

Insert Figure 1 about here

All ten equations contain quadratic tranformations of some of the basic variables, since hypotheses were developed to predict the functional form or "shape" of the variable relationship as well as the direction of the effect.

In addition to this complication, the model contains several non-recursive causal paths, due to the likelihood of reciprocal causal effects by innovation on several of the primary causal variables. As a whole, the system of equations is block recursive (Duncan, 1975), and since the equation for motivation to innovate forms a recursive block, it can be estimated consistently using OLS. The other equations, however, form a non-recursive system, and they require a more general procedure to obtain consistent estimates -- two-stage least squares, three-stage least squares, maximum likelihood, or some other efficient estimation procedure (Joreskog and Sorbom, 1981; Bagozzi, 1980). Using both basic variables and their nonlinear tranformations, all of the equations in Figure 1 pass both order and rank conditions for identification (Johnston, 1972; Goldfeld and Quandt, 1972).

The two principal hypotheses regarding the effect of individual job mobility on individual innovation tested in this study are illustrated in Figure 2.

Insert Figure 2 about here

The first principal hypothesis relates individual innovation to the

time a job holder has spent in his or her current job. Two theorists have developed quite different models of how job changes affect individual innovation. Schein (1971) argues that job holders pass through two stages in their jobs -- socialization and innovation. (While Schein lists "becoming obsolete" as a third substage, he doesn't discuss it in much detail.) Schein's argument leads to a simple conclusion: the longer a person's job tenure the more innovative she should be.

Katz (1980) has developed a more complex three-stage model of job tenure. In his view, socialization and innovation eventually give way to a third stage called "adaptation," and innovation by job holders starts to decline. This point of view is more consistent than Schein's with the research relating project-team age to innovation, as well as the various theories relating organizational mobility to innovation.

In general, empirical research on job tenure effects has been disappointing. Most cross-sectional studies have found small or negligible effects of time in job on such dependent variables as job satisfaction or performance (Schneider, Hall, and Nygen, 1971; McKelvey and Sekaran, 1977; Katz, 1978). Katz, for example, found no significant differences between short-tenured and long-tenured job holders in job satisfaction, organizational satisfaction, or task dimensions such as task identity or autonomy. (He did find that task dimensions are more strongly correlated with job satisfaction for individuals with less than two or three years tenure than for long-time jobholders.)

On the other hand, the few longitudinal studies of job tenure

effects have shown stronger effects than the cross-sectional studies. Haga, Green, and Danserau (1974), for example, found that the amount of "negotiating latitude" in supervisor-subordinate dyads is determined before the second month in a new job and remains fairly stable for at least nine months thereafter. The same study also demonstrated that managers' satisfaction with their jobs declines steadily week to week, along with the intrinsic appeal of their work, their interpersonal relations with supervisors, and the importance of job performance rewards to their sense of well-being. Keller and Holland (1981) compared difference scores for a group of professionals in an industrial R&D lab who had changed jobs with a control group of professionals who had not and found that innovativeness, performance, and job satisfaction were all higher for job changers than for stayers (although nonequivalence of the two groups raises questions about the validity of their results).

Following Katz, a curvilinear ⌒-shaped relationship between time in job and innovation is expected in this study. This prediction is suggested not only by Katz and the other researchers cited above, but also by eight specific hypotheses of the individual innovation model. These hypotheses are as follows:

1a. Time in job is expected to have a positive, decreasing marginal effect on job-related expertise. Job-related expertise, in turn, is expected to have a positive, decreasing marginal effect (⌒) on innovation. Thus, time in job should have a positive, decreasing marginal

indirect effect on innovation through job-related expertise.

1b. Time in job is expected to have a curvilinear, ⌒-shaped effect on user understanding. User understanding, in turn, is expected to have a positive, increasing marginal effect on innovation. The overall indirect effect of time in job on innovation through user understanding depends on the relative strength of these two effects. It is expected to be positive with decreasing marginal effect (⌒).

1c. Time in job is expected to have a negative effect on diversity of information sources. Diversity of information sources, in turn, is expected to have a positive effect on innovation. Thus, time in job should have a negative indirect effect on innovation through diversity of information sources.

1d. Time in job is expected to have a negative effect on job involvement. Job involvement, in turn, is expected to have a positive, increasing marginal effect on innovation. Thus, time in job should have a negative, increasing marginal indirect effect (⌒) on innovation through job involvement.

1e. Time in job is expected to have a negative, decreasing marginal effect on openness to change. Openness to change,

in turn, is expected to have a positive effect on innovation. Thus, time in job should have a negative, decreasing marginal indirect effect (⌒) on innovation through openness to change.

1f. Time in job is expected to have a ∩-shaped effect on search resources. Search resources, in turn, are expected to have a positive effect on innovation. Thus, time in job should have a ∩-shaped indirect effect on innovation through search resources.

1g. Time in job is expected to have a positive effect on implementation resources. Implementation resources, in turn, are expected to have a positive effect on innovation. Thus, time in job is expected to have a positive indirect effect on innovation through implementation resources.

1h. Time in job is expected to have a negative effect on job slack. Job slack, in turn, is expected to have a ∩-shaped effect on innovation. Thus, time in job is expected to have a ∪-shaped indirect effect on innovation through job slack.

Taking all these effects together, and holding other things equal (including career breadth), time in job is expected to have a ∩-shaped effect on innovation. It should increase when an

individual first takes a new job, flatten out after a while, and begin to decline as time in job continues to increase.

The second principal hypothesis relates innovation to the breadth of a person's career history. The division of labor implies that the narrower a person's career path, the more efficient and productive she should be in her work. If the criterion is innovation rather than efficiency, however, the value of specialization could be considerably less. Indeed, a number of researchers have suggested that, up to a point, broader career paths should stimulate more innovation (Peres, 1966; Jennings, 1967; Hall, 1976; Graen, 1976; Ouchi and Johnson, 1978).

Career breadth is expected to have a positive effect on innovation in this study. Besides the general arguments given by the researchers cited above, this prediction is suggested by three specific hypotheses tested in the individual-level innovation model. These hypotheses are as follows:

2a. Career breadth is expected to have a positive effect on user understanding. User understanding, in turn, is expected to have a positive, increasing marginal effect on innovation. Thus, career breadth is expected to have a positive, increasing marginal indirect effect (⌒) on innovation through user understanding.

2b. Career breadth is expected to have a positive effect on diversity of information sources. Diversity of information sources, in turn, is expected to have a positive effect on

innovation. Thus, career breadth is expected to have a positive indirect effect on innovation through diversity of information sources.

2c. Career breadth is expected to have a positive effect on implementation resources. Implementation resources, in turn, are expected to have a positive effect on innovation. Thus, career breadth is expected to have a positive indirect effect on innovation through implementation resources.

Taking these effects together, and holding other things equal (including time in job), the broader an individual's career path, the more innovative he or she should be.

The implications of these individual-level hypotheses for the effects of organizational mobility patterns on organizational innovation are clear. Figure 3 illustrates the relationship between individual and organizational levels of analysis in this study.

Insert Figure 3 about here

On the input (cause) side, organizational variables like mobility rates or degree of cross-functional job rotation are directly linked with the two individual mobility variables investigated in

this study. (For example, the greater an organization's average mobility rate, the shorter the average time in job of its employees). On the output (effect) side, innovation by individuals is assumed to be one source of organizational innovation. (Obviously, it is not the only source. Many other factors -- project-team attributes, organizational climate and culture, etc. -- are presumably important to organizational innovation as well.) Thus, one way that organizational mobility patterns can affect organizational innovation is through the effects of individuals' job moves on individual innovation.[3]

While Schein's theory of job tenure effects implies that mobility is bad for innovation, Katz's theory implies that innovation requires a moderate amount of mobility -- neither too much nor too little. For Schein, the fewer members an organization has going through socialization, the more innovative the organization should be. For Katz, the fewer members an organization has in the socialization and adaptation stages, the more innovative it should be.

DATA COLLECTION AND RESEARCH SITE

Data to test the individual-level innovation model and the mobility hypotheses discussed above were collected at a single large research and development laboratory located just outside a medium-size industrial city in the Midwest. Four data collection methods were employed in the study:

1. Self-reports from scientists and engineers on a rather extensive questionnaire.
2. Rankings by first-line supervisors ("section managers") of their professionals on several different criteria (obtained in structured interviews).
3. Ratings by professionals of their colleagues on several different criteria.
4. Short, unstructured interviews of professionals and their managers. (These interviews were intended to probe widely-held beliefs about enhancers and inhibitors of innovation in the lab. They were not used in the analysis.)

The questionnaire, the main data collection instrument used in this study, was quite lengthy, typically requiring between two and three hours to complete. It was split into two parts, one of which was called the "Contribution Log," and the other the "Questionnaire."

The Contribution Log was essentially a sheet of lined paper split into five categories, with the lines numbered separately within each category. The five categories were labeled:

- Product Contributions
- Process Contributions
- Administrative Contributions
- Knowledge Building Contributions
- Other Contributions

Respondents were asked to think back over the past week of work and list on separate lines every contribution they made to the projects

they had worked on or the lab as a whole during that week. The instructions stressed that respondents should try to list every contribution they had made, no matter how small, and should not worry about the importance or novelty of the contributions they listed. The categories were intended to jog respondents' memories and elicit contributions they might otherwise have forgotten. They were given about 10 minutes to complete these logs, and then the Questionnaire was passed out.

The Questionnaire was divided into 14 parts. After a brief section on general background, respondents were asked to fill out one "Contribution Rating Sheet" for each contribution they had listed in their contribution logs. These rating sheets asked for a good deal of information about each contribution, including subjective ratings of its novelty and importance, information about its history, how far along it was toward implementation, and the degree of personal responsibility respondents felt for the contribution. The next section of the questionnaire asked respondents to give a fairly complete career history (indicating several facts about each job they had held), starting from the time they received their last full-time degree. Following this was a sociometric section adapted from Tichy, Tushman, and Fombrun (1980). Three of the next ten sections asked respondents to rate their peers on seven different criteria. The remainder of the questionnaire asked for various types of subjective data, including work and job attitudes, assessments of the importance and availability of various resources, brief descriptions of innovations which they had been involved with previously at the

lab, and information about their professional goals and targets.

Both of these instruments were administered to respondents in their primary work groups, called "sections." (This was done not only for convenience but also to facilitate confidential coding of the peer ratings.) Sometimes two or three sections were combined for purposes of administering the instrument. The groups thus assembled varied in size considerably - from as few as two to as many as 24.

In addition, the section managers (first-line supervisors) for almost all the participants were interviewed for about one-half hour each. During these interviews, managers were asked to rank the scientists and engineers who worked for them on six different criteria. They also indicated which projects their subordinates had been assigned to during the previous month and answered one or two open-ended questions about innovation in the lab, as well.

Participation in the study was quite good. Of 591 project engineers and scientists in the lab's seven discipline-based divisions, 264 completed usable questionnaires, for an overall response rate of just under 45%. In addition, 60 of the lab's 83 section managers (72%) were interviewed about the professionals who worked for them. A broad cross-section of the lab was covered by both questionnaires and interviews, except for one division where management was not supportive of the study. Participation rates for the other six divisions ranged from 38% to 73%.

The scientists and engineers in this sample are mostly middle-aged (median years in work force is 14), and they have spent most of their careers working at the company (median years at the

company is 13). Over one-third (34%) have completed doctorates, and another 27% have completed masters degrees. Their functional specialties range broadly, including mechanical engineers, electrical engineers, mathematicians, chemists, physicists, and a number of other disciplines.

The lab itself was in a period of slow contraction at the time of the study (which has accelerated since then), and the unstructured interviews revealed some concern about its future. Interestingly, dissatisfaction with the climate for innovation at the lab was greater among the section managers than among the project engineers and scientists, a reversal of the common finding that hierarchical level is positively related to satisfaction with the organization (Cummings and Berger, 1976).

IV. MEASUREMENT MODEL RESULTS

Before the structural equation model of individual innovation could be tested, measures of the key variables had to be developed and checked for convergent and discriminant validity (Campbell and Fiske, 1959; Cook and Campbell, 1979; Bagozzi, 1980; Phillips and Bagozzi, 1981). The complexity of the data - multiple sources, various collection methods, etc. - made this step more critical and more difficult than in most organizational research.[4]

Measures developed from these sources had to be compared and refined in several stages to meet acceptable reliability and validity standards. In Bagozzi and Phillips's (1982) terms, this process generally began at the mono-method level and then moved to

the multi-method level of analysis.

Seven of the 25 variables in the structural equation model of individual innovation are assumed to be measured without error. These variables are:

(1) Career breadth (BRED)

(2) Level of education (EDUC)

(3) Hierarchical level of job (HIER)

(4) Proximity to project deadline (PDEAD)

(5) Time in job (TIJ)

(6) Years in the company (YRCO)

(7) Years in the work force (YRWF)

The measures used for these seven "error-free" variables are listed in Table 3.

Insert Table 3 about here

The other 18 variables contained in the structural equation model of individual innovation are assumed to be subject to measurement error. Each variable was modeled with multiple measures, using the confirmatory factor analysis submodel of Joreskog and Sorbom's LISREL V program. Once a satisfactory fit was obtained for each measurement model, a composite measure (or measures) was computed using factor score regression coefficients obtained from the program (Joreskog and Sorbom, 1981, p. III.21). These estimated factor scores were then used to test the structural

equation model.

Table 4 summarizes results of testing all eighteen measurement models and gives estimated reliabilities of composite measures for each variable.

Insert Table 4 about here

As this table shows, confirmatory factor analysis produced a number of surprises. For seven of the eighteen variables, single-factor measurement models did not fit the measures. For these variables, the assumption of unidimensionality is violated (Bagozzi and Phillips, 1982), and they had to be treated as multidimensional constructs.

The measurement model for motivation to innovate (MOTINN) provides one of the most interesting examples of multidimensionality. Since a single-factor model did not fit the nine measures well (χ^2=61.6; df=27; p<.001), a model with two underlying factors was tested. One factor reflects respondents' tendency to choose problems where they can get acceptable results, even though not spectacular, and to concentrate on finding immediate solutions to problems. This factor, reversed in sign, and called "solution aspiration level," fits the original definition of motivation to innovate fairly well. The other factor, however, called "abstract/concrete thinking," contains items which reflect respondents' problem-solving style, especially

their tendency to search for and use abstract, general principles when solving concrete problems. The two-factor model not only proves that these two underlying factors are distinct, but it also provides an estimate of the correlation between them. In this case, the estimated correlation is negative (-.26), indicating that respondents who have relatively high aspiration levels for solving problems in innovative ways are less likely to search for abstract principles in their work than members who have relatively low aspiration levels for solutions.[5]

Another surprise revealed by the measurement modeling was the lack of convergent validity for some well known, often used measures. For example, Budner's (1962) 16-item scale for intolerance of ambiguity was used as one set of measures for personal commitment to innovation (PCI) in this study. Using Budner's technique of summing item scores to arrive at an aggregate measure of intolerance for ambiguity, this sample has a higher mean score (i.e., less tolerance for ambiguity) and a lower variance than most of Budner's validation samples. On the face of it, this seems surprising for a sample of R&D scientists and engineers. When the 16 questions were tested using confirmatory factor analysis, however, a model containing a single underlying factor fit the data poorly (χ^2=217; df=104; p<.001). A three-factor model based on Budner's theoretical distinction between insoluble, complex, and novel situations was then tested, but this did not converge to a solution at all. Finally, a second-order factor model with three first-order factors and one second-order factor was made to fit by dropping 7 of the 16 original questions,

constraining several parameters to avoid infeasible solutions (the so-called Heywood case -- Jackson and Chan, 1980), and allowing several cross-factor loadings and correlated errors (χ^2=33.8; df=25; p=.11). By the time all these changes were made, however, the model bore little resemblance to Budner's original theory. Intolerance of ambiguity, as Budner defined and measured it, simply does not have convergent validity in this sample.

Space limits preclude a detailed description of the measurement models for all 18 variables shown in Table 4. Interested readers should consult Anderson (1984) for this information. Since individual innovation is the key dependent variable for the structural equation model, however, it seems worthwhile to present its measurement model here. This model, a second-order common factor model with five first-order factors and one second-order factor, is illustrated in Figure 4 with standardized coefficients. The five first-order factors in this model are methods groupings of the ten different innovation measures.

Insert Figure 4 about here

Ratings by managers load strongly on the second-order innovation factor (.82). Managers were asked to rank the professionals who worked for them on several different criteria, two of which (innovativeness and productivity) were hypothesized to

measure innovation. These ranks were then converted to Z-scores using a modified version of Guilford's normalized-rank scaling method (Guilford, 1954). Kolmogorov-Smirnov goodness-of-fit statistics of .81 for both scales confirmed that the transformed Z-scores thus obtained were in fact distributed approximately N(0,1). In the innovation measurement model, managers' transformed innovativeness rankings load .91 and their transformed productivity rankings load .72 on the first-order manager rating method factor.

The peer rating method factor also loads strongly on the second-order innovation factor (.79). Peers rated each other on seven different criteria, two of which were hypothesized to measure innovation. Respondents were asked to indicate how innovative each of their peers was on a 7-point Likert scale. They were also asked to estimate the number of weeks it had been since they were last impressed by a novel, useful insight from each of their peers. Since most respondents were rated by more than one colleague, interrater reliabilities for these ratings could be estimated. The innovativeness scale has an interrater reliability of .69, and the reliability of raters' estimates of "weeks since last innovation" is .60. In the innovation measurement model, peers' innovativeness ratings load 1.00 (i.e., with no error) and peers' estimates of weeks since last innovation load -.60 on the first-order peer rating method factor.

A group of three patent activity measures loads moderately on the second-order innovation factor (.51). Respondents were asked how many patent disclosures they had filed in the previous year (1981), how many disclosures they had filed in the last five years,

and how many patents they had received (or which were still pending or applied for) in the last ten years. The number of disclosures filed in the previous year loads most strongly on the first-order patent method factor (.89), followed by the number of disclosures filed in the last five years (.81), and the number of patents received in the last ten years (.46).

Information provided by respondents in their Contribution Logs was also used to measure innovation. The contribution log method factor loads moderately on the second-order innovation factor (.46). The total number of contributions listed by respondents loads .89, and the number of contributions which respondents indicated were already implemented loads .80 on this factor. While these measures are rather gross, they provide interesting confirmation of the hypothesis that innovation is evident in the day-to-day contributions which scientists and engineers make to their work.

The last measure, a single self-report item, loads weakly on the second-order innovation factor (-.19). Respondents were asked to estimate how long it had been since they were last complimented by a colleague for a clever idea. Although the loading is small, it is significant ($t=-2.59$; $p<.05$). As expected, the factor loading is negative, indicating that innovative respondents reported more recent compliments than less innovative respondents.

The innovation measurement model fits the covariance matrix for all ten measures quite well ($\chi^2=38.6$; $df=29$; $p=.11$; Incremental Fit Index = .986). It departs from the *a priori* method factor groupings in three minor ways. Since patent awards

contribute to professionals' reputations for innovation with their colleagues, the number of patents received during the last ten years was allowed to load weakly on the peer-rated innovation factor (.20). Errors between two pairs of measures were also allowed to correlate with each other, but both of these correlations are small (.18 and -.10). Without these three refinements, the chi-square jumps to 78.6 ($df=32$; $p<.001$), but the incremental fit index drops only .06, from .98 to .92. Thus, the second-order single-factor measurement model for innovation is quite robust.

STRUCTURAL EQUATION MODEL RESULTS

Once measurement models were estimated and convergent validity was established for the eighteen unobserved variables assumed subject to measurement error, factor score composites were computed for each of them. These composites were then combined with the seven observed variables assumed to have no measurement error in order to estimate the structural equation model. Although it departs from Bagozzi and Phillips's (1982) holistic construal, separate estimation of measurement and structural models was used primarily because of the nonlinear relationships hypothesized in the model. In order to estimate curvilinear relationships, quadratic transformations of the basic variables were calculated and included in the structural model. If the measurement models defined for these basic variables are assumed to be linear, then the measurement models for the quadratic terms must be nonlinear in

the parameters, since it is inconsistent to assume that the same variable X is measured differently when it is transformed to X^2 than when it stands alone. Since nonlinearity of parameters violates the assumptions of LISREL (a linear model), and since nonlinear estimation procedures for simultaneous estimation of measurement and structural equation systems have not been developed, the two-stage approach was adopted.

A second departure from Bagozzi and Phillips's holistic construal was necessitated by the size of the structural equation model itself. Simultaneous estimation of all 10 equations was simply not feasible given reasonable computation resources. Thus, two stage least squares was used to estimate each equation in the system separately. The main advantage of 2SLS is that it can provide consistent parameter estimates for equation systems which cannot be estimated by a more comprehensive technique (e.g., three stage least squares, maximum likelihood, generalized least squares). The main disadvantage is that 2SLS estimators are less efficient than most of the other multiple equation estimation procedures (Johnston, 1972).

Because the structural equation model is large, the discussion of results that follows will be limited to the main equations and parameters of interest (i.e., those pertinent to the hypotheses discussed above). Readers interested in the complete model results should consult Anderson (1984).

Results of testing two different structural models are presented below. The first model is a single-equation model with the fourteen exogenous variables regressed directly on the main

dependent variable, innovation. This is called the "reduced model." The reduced model is simply a multiple regression model testing the effects of time in job and career breadth on innovation, while controlling for the linear effects of a number of covariates hypothesized to influence innovation directly. The second model, called the "full model," is a modified version of the ten-equation structural equation model shown in Figure 1. The full model constrains the effects of time in job, career breadth, and the other exogenous variables on innovation by, in a sense, channeling these effects through the primary causal variables. The full model can therefore be viewed as a more structured version of the reduced model, more informed by theory and less prone to specification error. On the other hand, since the full model is more constrained, the total effects of the exogenous variables on innovation (i.e., the sum of the indirect paths by which they affect innovation) are likely to be weaker than their direct effects in the reduced model.

The full model helps alleviate another major drawback of the simple multiple regression approach used in the reduced model -- the problem of inferring causality from a covariance structure. With the reduced model, causality is difficult to establish. For example, if the regression coefficient of career breadth is significant, is it because career breadth has a positive effect on innovation, as hypothesized, or is it because more innovative people like to move around more? The theory which determines the choice of covariates for the regression model helps establish some basis for inferring causality. The structure of the full model,

however, strengthens the case, because the significant relationships in this model are more structured by theory than in the reduced model. If the total effect of career breadth on innovation in the full model is positive, it is more likely that career breadth affects innovation through the hypothesized intervening variables than that innovation has a reciprocal effect on career breadth through these same intervening variables. Reciprocal causality is not impossible, but it is less likely than in the unconstrained multiple regression.

Reduced Model Results

Table 5 shows the results of testing the reduced model using ordinary least squares (OLS).

Insert Table 5 about here

The model is highly significant ($F_{20,133}=5.52$; $p<.001$), and the fourteen predictor variables explain about 37% of the variance in innovation ($R^2=.453$; $\bar{R}^2=.371$). Eight of the fourteen predictors are significant at the .10 level or better.

The measure of career breadth used in the reduced model (number of changes in functional area) has a positive effect on innovation, as expected, which is significant at the .05 probability level ($t_{133}=2.48$). According to the OLS estimate,

each functional change should increase innovation by about .15σ. (Presumably, there is an upper limit to this effect. The maximum number of functional changes for anyone in the sample was nine.) While time in job has a significant effect on innovation in the reduced model (t_{133}=2.80; p<.01), the effect is positive, not $\cap$-shaped as hypothesized. Furthermore, the effect is small: according to the coefficient estimate, an extra ten years in a job should increase innovation by about .35σ.

Among the other significant variables, hierarchical level has a significant and strong positive effect on innovation (t_{133}=5.19; p<.001). Its coefficient indicates that a senior engineer should be almost .6σ more innovative than an engineer. While an indirect effect of hierarchical level on innovation was predicted, its strength is somewhat open to question because of the possibility of reciprocal causality. Since promotions to senior technical positions are influenced by individual innovation in most R&D labs, innovation probably has a positive effect on hierarchical level. Some of the apparent effect of hierarchical level on innovation in the reduced model is probably due to this reciprocal effect, and the size of the coefficient in the OLS regression is probably biased upwards.

Years in the work force also has a strong, significant effect on innovation in the reduced model, but the effect is negative rather than positive (t_{133}=-3.50; p<.001). Furthermore, this effect is dramatic: other things equal, every decade a professional spends in the work force should reduce her innovation by about .33σ. This effect may reflect the process of technical

obsolescence in older scientists and engineers (Margulies and Raia, 1967; Rothman and Perucci, 1970).

Among the other predictor variables in the reduced model, time horizon of professional goals has a significant $\frown$ -shaped effect on innovation ($F_{20,133}=4.82$; $p<.01$). Innovation is highest when professionals set their goals a little more than 2 years in the future. An increase in time horizon from 2 to 3 years, however, reduces innovation by only about $.01\sigma$, and a decrease in time horizon from 2 years to 1 year reduces innovation by only about $.03\sigma$. Professionals' belief that performance is rewarded (one of the two factors for career relevance of job) also has a significant $\frown$-shaped effect on innovation ($F_{20,133}=4.04$; $p<.05$), although it too is weak. Innovation is highest when professionals are in the middle of this scale, and those who fall one standard deviation away from the mean are likely to be $.1\sigma$ to $.2\sigma$ less innovative. It appears that realism (or even moderate cynicism) about the relationship between performance and rewards is characteristic of innovative performers.

The proximity to current project deadline also has a significant curvilinear effect on innovation in the reduced model ($F_{20,133}=4.55$; $p<.05$), although here the effect is $\smile$-shaped. Scientists and engineers working at the beginning or end of their projects are apparently more innovative (by about $.8\sigma$) than those working at the 60% complete point (the point of maximum innovation). This surprising finding may be best explained by a selection argument. Since the number of professionals assigned to a project generally rises and then falls, the professionals who

join the project for short stretches in the middle (when more "bodies" are needed) may be less innovative than those who start and finish the project (e.g., project managers).

Finally, the effect of education on innovation is significant at the .10 probability level in the reduced model($F_{20,133}=2.87$), although rather than a clear positive effect, it has a surprising ∪ shape, with a minimum at a master's degree level. One explanation for this finding lies in the significant correlation between education and hierarchical level (.50). If hierarchical level is dropped from the reduced model, education has the same ∪-shaped form, but the effect is much weaker, and the point of minimum innovation drops to .4 degrees (i.e., less than a bachelor's degree).

Perhaps the most surprising result of the reduced model is the lack of effect for some traditional job characteristic variables. Neither autonomy nor support for innovation has a significant effect on innovation.

Full Model Results

OLS and 2SLS estimates for the innovation equation of the full model (equation 1 in Figure 1) are given in Table 6.

Insert Table 6 about here

Four modifications were made to the original structural equation model based on results from the measurement models and analysis of the correlation matrix of structural variables. Table 6 reflects these modifications.

In the case of three variables -- openness to change, motivation to innovate, and implementation resources -- mono-method measurement models revealed the presence of two underlying and largely independent factors, rather than just one. Rather than choosing arbitrarily one factor to use in the structural equation model for these variables, both were included. Thus, three new variables appear in the innovation equation shown in Table 6. They are:

- Acceptance for new ideas -- respondent's perception of the ease with which his/her new ideas were accepted and implemented (correlates .25 with openness to change)
- Solution aspiration level -- respondent's disdain for problems where he/she can get immediate solutions and merely acceptable results (correlates -.26 with the other factor derived from motivation to innovate -- "abstract/concrete thinking")
- Sponsorship resources -- the number of sponsors respondent has inside and outside the lab and the strength of their support (correlates .33 with implementation resources)

The fourth modification to the innovation equation was the substitution of three exogenous variables -- education level, time

in job, and years in the work force -- for the primary explanatory variable, job-related expertise. A quick scan of the correlation matrix for the structural variables revealed a very high correlation between innovation and job-related expertise (.83). Since manager and peer ratings play a major role in both factors, the possibility of a ratings halo effect was indicated. Therefore, the intercorrelation matrix of innovation and expertise ratings was analyzed using Campbell and Fiske's (1959) multi-trait multi-method approach. The average cross-variable, within-method correlation for peer and manager ratings was .68, while the average within-variable, cross-method correlation was only .47, lending support to the halo effect hypothesis. Because of this methods bias, the job-related expertise variable was replaced with its three main determinants in the innovation equation and job-related was dropped from the structural equation model.

As Table 6 shows, when estimated under OLS, the innovation equation is highly significant ($F_{16,178}=6.02$; $p<.001$), although it explains a relatively small amount of the variance in innovation (about 29%). Since the proportion of variance explained in this equation is smaller than the variance explained in the reduced model (about 37%), the total effect of all exogenous variables (including time in job and career breadth) on innovation in the full model is certain to be smaller than their effect on innovation in the reduced model. In other words, forcing the exogenous variables to influence innovation through the primary causal variables has reduced their potential effect on innovation by a substantial amount. This suggests that the theory of individual

innovation has left out one or more important paths by which the exogenous variables influence innovation. An alternative explanation, however, is that the primary causal variables contain more measurement error than many of the exogenous variables in the model, and measurement error in these variables is likely to lower their structural coefficients in the model (Bagozzi, 1980).

Nine of the fourteen predictor variables in the innovation equation are significant at the .05 probability level or better using OLS estimation. The effect of 2SLS estimation, however, is dramatic: standard errors of coefficient estimates are increased so much that only four variables are significant at the .10 probability level or better. These weaker relationships are reflected in a higher standard error of estimate for the 2SLS regression. (Standard error of estimate is .922 with 2SLS estimation, compared with .827 with OLS regression. There is no overall goodness of fit test for two stage least squares.) The other general effect of 2SLS is to raise a number of coefficient estimates (while simultaneously raising their standard errors), especially those for variables like openness to change and motivation to innovate which had more than one factor entered in the model.

Under 2SLS, both abstract/concrete thinking and solution aspiration level have effects on innovation that are significant at the .05 probability level ($t_{149}=2.53$ and $t_{149}=2.03$, respectively). However, these effects are positive (direct) rather than $\cap$-shaped, as hypothesized. The greater a scientist's or engineer's tendency to apply abstract ideas to concrete problems

and the more ambitious she is about the problems she takes on (characteristics which are negatively correlated in the sample), the more innovative she is likely to be. The coefficient estimates indicate that professionals whose abstract/concrete thinking is one standard deviation above the mean are likely to be .3σ more innovative than average, and professionals whose solution aspiration level is one standard deviation above the mean are likely to be .2σ more innovative than average.

Education level has a weak positive effect on innovation under 2SLS estimation (t_{149}=1.78; p<.10), and its coefficient indicates that the addition of a degree is likely to add about .2σ to an individual's innovation. Openness to change also has a significant positive effect on innovation (t_{149}=1.94; p<.10), and its coefficient indicates that professionals who are one standard deviation above the mean in openness are likely to be .5σ more innovative than average.

Results of OLS and 2SLS estimation for the innovation equation and the eleven other equations in the structural equation model are summarized in Table 7.

Insert Table 7 about here

Under OLS estimation, eight of the twelve equations are significant at the .001 probability level or better. Of these, the equations for innovation, job involvement, abstract/concrete thinking, user

understanding, and sponsorship resources have the highest adjusted $\bar{R}^2$s: in these five equations, the hypothesized predictor variables explain 15% or more of the variance in the dependent variable (under OLS). The equations for diversity of information sources, search resources, and implementation resources, although significant under OLS, have very low adjusted $\bar{R}^2$s, indicating that the determinants of these factors are not captured by the predictor variables in the model. Two stage least squares estimation increases the average standard error of estimate for the nine equations estimated under both 2SLS and OLS from .943 to .956, reflecting generally higher standard errors for coefficient estimates under 2SLS.

Figure 5 shows the standardized coefficient estimates for the two time in job measures -- time in job and time in current technical area -- for all the equations in the model. It also gives an estimate for the total effect of both variables on innovation through their multiple paths.

Insert Figure 5 about here

The only statistically significant effect of time in job is a negative effect on job slack (t_{184}=-2.31; $p<.05$). Since the effect of job slack on innovation is small (and nonsignificant), this path contributes little to the variance of innovation. Taking all paths together, the estimated total effect of time in job on

innovation in the full model is .077 (standardized), which is not significantly different from 0. Even if it were significant, the magnitude of the effect is obviously small. Staying in a job for an extra ten years would increase innovation by only about .1σ.

Time in technical area has a significant $\frown$-shaped effect on user understanding ($F_{5,160}=4.89$; $p<.01$). User understanding rises for the first 10 to 15 years a job holder spends in a technical area, peaks at about 16 years, and then begins to decline slowly. Time in technical area also has a similar $\frown$-shaped effect on job involvement ($F_{160}=5.86$; $p<.01$), with a maximum at about 19 years. Since neither user understanding nor job involvement has a significant effect on innovation, however, the total effect of time in technical area is also small. Taking all paths together, the estimated total effect of time in technical area on innovation has a fourth-degree polynomial form, as shown in Figure 5, but one which can be closely approximated by a linear coefficient of .07. As with time in job, the total effect of time in technical area is small in magnitude and not significantly different from 0. Even if the effect were significant, staying in a technical area for an extra ten years would decrease innovation by less than .1σ.

Figure 6 shows standardized estimates of the effects of five career breadth measures contained in the full model.

Insert Figure 6 about here

As with time in job, the effects are generally quite small, and only a few achieve statistical significance. The number of projects worked on has a significant positive effect on user understanding ($t_{161}=2.78$; $p<.01$), and the number of projects worked on per year spent in the company has a significant positive effect on diversity of information sources ($t_{161}=2.47$; $p<.05$). Since neither user understanding nor diversity of information sources has a significant effect on innovation, however, the contribution of these career breadth measures to innovation is small and not statistically significant. The same is true for the other three career breadth variables in the full model. Taken together, three of the four project-related measures of career breadth have small positive total effects on innovation, while number of jobs held per year spent in the company has a small negative total effect on innovation. (None of these effects are statistically significant.)

DISCUSSION

It is difficult to escape the conclusion that neither time in job nor career breadth affects innovation very strongly in this sample of scientists and engineers. While five of the seven path-specific hypotheses concerning time in job's effect on innovation were confirmed directionally, none reached statistical significance. Similarly, while two of the three path-specific hypotheses concerning career breadth's effect on innovation were confirmed directionally, all of these effects were also weak.[7]

There is some consistency between the reduced model and the full model in that time in job appears to have a small positive effect on innovation. This finding is more consistent with Schein's two-stage model of job socialization effects than with Katz's three-stage model.

On the other hand, remaining in a particular technical specialty or functional area may eventually be detrimental to innovation. The negative effect of time in technical area is consistent with the effect of years in the work force on innovation in both models. The total effect of years in the work force in the full model, while smaller in magnitude than in the reduced model, is still negative: an extra ten years in the work force is estimated to decrease innovation by $.1\sigma$ to $.2\sigma$. Combined with the positive effect of change in functional area on innovation in the reduced model, these findings lend support to the concept of technical obsolescence and suggest that one or two changes in technical function in the course of an R&D professional's career may result in more innovation than a one-dimensional career track.

Because the individual-level effects of time in job and career breadth are weak, it is difficult to draw conclusions about the types of organizational mobility patterns that might enhance or inhibit organizational innovation. From the findings about time in technical area discussed above, one might infer that organizations which facilitate shifts in R&D professionals' technical specialties once or twice during their careers might be more innovative than organizations which force them (or allow them) to remain in their original specialties forever. On the other hand, the bulk of the

findings in this study cast some doubt on the growing popularity of theories which suggest that rapid movement and broad mobility patterns stimulate organizational innovation. Instead, they hearken back to older ideas which emphasize the longevity and sustained commitment to organizational roles that is needed to support innovation.

Perhaps the most interesting finding of this study is that a number of individual motivation and attitude variables have important effects on innovation. The reduced model shows that time horizon of professional goals and belief that performance is rewarded both have significant ⌒-shaped effects on innovation. In the full model, abstract/concrete thinking, solution aspiration level, and openness to change all have significant positive effects on innovation. The effect of personal commitment to innovation on innovation approaches significance in both reduced and full models. (In the full model, it has an accelerating ⌒-shaped total effect.)

These results suggest that it may be time to bring the individual back into innovation research. The earliest innovation studies examined diffusion processes among individual farmers. This led to considerable research effort spent identifying and analyzing the characteristics of individuals which appear to affect adoption (e.g., cosmopolitanism). As interest in innovation grew, however, theories were developed about the diffusion of innovations through organizations rather than individuals. The organization became the unit of analysis, and the focus of research shifted to organizational characteristics like size and centralization (e.g.,

March and Simon, 1958; Mansfield, 1963; Thompson, 1965; Mohr, 1969). As a result of this shift, in the past two or three decades relatively little innovation has studied the effects of individual styles and attitudes on innovation. Only the research on creativity in psychology and education focused squarely on the individual, but this literature has rarely examined the innovation process in any concrete detail. (Furthermore, the study of creativity has been flawed by major conceptual and validity problems -- McNemar, 1964; Ebel, 1973). It may be time to reconsider the role of individuals and individual differences in initiating and implementing innovations.

The other interesting finding of this study, alluded to above, is that job characteristic variables like autonomy, career relevance of job, support for innovation, and even time in job have such weak effects on innovation. These results suggest that the traditional concept of a job may not be very applicable to R&D labs. Most of the scientists and engineers in this sample have enough autonomy to "evolve" their jobs in various directions (Miner, 1980). In such an environment, a job is a kind of umbrella description covering whatever combination of projects or assignments a professional wants to undertake and can find funding for. One might think that in a project-based organization like an R&D lab, project assignment patterns would have stronger effects on innovation than formal changes in job title. In this lab, however, professionals were typically assigned to multiple projects at the same time, and the effects of project assignments were diffuse. Even so, the project-based measures of career breadth had stronger

effects than the job-based measures of career breadth in this study.

In general, the results of this study show once again how difficult it is to test longitudinal hypotheses like the effects of job tenure or career progression using cross-sectional data (Baltes and Nesselroade, 1973; Huston-Stein and Baltes, 1976; Rogosa, 1979). Individual differences inevitably introduce substantial random error into the variable relationships, causing them to regress toward the mean (Bock, 1975). Without longitudinal data, it is impossible to use individual respondents as their own controls as they progress through a job or a career (Cronbach and Furby, 1970). Even if strong effects had been found, the reliance on cross-sectional data would make it difficult to rule out differential selection or attrition as alternative explanations (Cook and Campbell, 1979).

Finally, the study also shows how incomplete our knowledge is about the causes of innovation in environments like industrial R&D labs. While a large structural equation model was able to explain 30-40% of the variance in individual innovation, the majority of variance was left unexplained by the model. Although some of this gap is certainly due to measurement error, even with perfect measures, a good deal of unexplained structural variance would undoubtedly remain.

VARIABLES HYPOTHESIZED TO AFFECT INNOVATION DIRECTLY

I. INFORMATION VARIABLES

Job-related expertise (JREXP) -- a job holder's technical competence that is directly relevant to performing job duties.

User understanding (USERUN) -- a job holder's understanding of the technical requirements and acceptance criteria for new ideas imposed by potential users.

Diversity of information sources (DIV) -- degree to which a job holder's total information network is spread out across a diverse group of sources.

II. MOTIVATION VARIABLES

Job involvement (JOBINV) -- importance of work in a job holder's self-image (Lodahl and Kejner, 1965).

Openness to change (OPEN) -- a job holder's cognitive and behavioral flexibility and his resistance to overcommitment effects (Salancik, 1977).

Motivation to innovate (MOTINN) -- a job holder's tendency to search for innovative rather than routine solutions to problems, given the nature of his job.

III. RESOURCE VARIABLES

Search resources (SCHRES) -- critical inputs to the search process provided by a job holder's task environment.

Implementation resources (IMPRES) -- critical inputs to the implementation process provided by a job holder's task environment.

Job slack (JOBSLK) -- amount of time available to a job holder which is free from the pressure of specific role demands.

Table 1

EXOGENOUS VARIABLES HYPOTHESIZED TO AFFECT INNOVATION INDIRECTLY

Autonomy of job (AUTNMY) -- amount of discretion, independence, and opportunity for personal initiative given a job holder (Hackman and Oldham, 1974)

Career breadth (BRED) -- diversity of a job holder's career history

Career relevance of job (CREL) -- relevance of a job holder's job to his career goals

Education level (EDUC) -- highest formal degree obtained by a job holder

Frequency of user contacts (FUC) -- frequency with which a job holder comes into contact with potential users of innovations he might develop

Hierarchical level of job (HIER) -- level of a job holder's job in the organizational hierarchy

Importance of current project (IMPPRJ) -- a job holder's perception of the importance of his major current project (if he has one)

Personal commitment to innovation (PCI) -- a job holder's general commitment to being innovative in his work

Proximity to current project deadline (PDEAD) -- nearness of a final deadline for a job holder's major current project (if he has one)

Professional orientation (PROFOR) -- a job holder's commitment to professional associations and societies outside the lab

Support for innovation in job (SUPINN) -- degree to which supervisors and higher level managers expect and support novel, innovative work from a job holder

Time-horizon of professional goals (THORZN) -- future time horizon which a job holder contemplates when establishing his professional goals and targets (El Sawy, 1983)

Time in current job (TIJ) -- number of months a job holder has spent in his or her current job

Years in the company (YRCO) -- total number of years a job holder has been employed by the company

Years in the work force (YRWF) -- total number of years a job holder has spent in the work force

Table 2

OPERATIONAL MEASURES FOR ERROR-FREE VARIABLES

1. Career Breadth (BRED)
   Six different measures, all of which were derived from career histories and other information provided by respondents in questionnaire:

   Number of changes in functional area while at company
   Number of projects worked on (total) while at company
   Number of projects worked on Years in company
   Number of major project changes while at company*
   Number of major project changes Years in company
   Number of jobs held in company Years in company

2. Education Level (EDUC)
   Highest educational degree obtained, coded as 0 for no degree, 1 for a bachelors, 2 for a masters, and 3 for a doctorate.

3. Hierarchical Level of Job (HIER)
   Respondent's rank in company hierarchy, from Associate Engineering Specialist (coded as 3), through six other ranks up to Advisory Engineer or Scientist (coded as 14).**

4. Proximity to Project Deadline (PDEAD)
   Respondent's estimate of percentage complete for his current project. If subtracted from 100%, measures time to expected completion relative to the overall length of time spanned by the project.

5. Time in Job (TIJ)
   Two different measures of time in current job:

   Time in job, counted from respondent's last change in job title which was accompanied by change in supervisor, physical location of desk, or salary grade.

   Time in technical area, based on response to the question, "How long have you worked in jobs which demand the same kind of technical expertise as your current assignment?"

6. Years in the Company (YRCO)
   Total number of years respondent has been an employee of company. (Periods of discontinuous employment were summed to arrive at this figure.)

7. Years in the Work Force (YRWF) -- Total number of years since respondent first entered the work force.

*A project change was called "major" if it involved a change in the physical location of respondent's desk or a change in respondent's supervisor or project-team leader.

**These code assignments reflect relative salary ranges.

SUMMARY OF MEASUREMENT MODELS

Variable	Model type	Number of measures	χ^2 (df), Sign level	Incremental fit index	Est. reliability of composite(s)
I. Dependent Variable					
Innovation	Second-order single-factor model	10	38.6 (29) p=.11	.98	.81
II. Primary Explanatory Variables					
Diversity of info. sources	Two-factor model (correlation between factors =.83)	8	17.9 (13) p=.16	.99	Factor 1-.76 Factor 2-.99
Implementation resources	Three-factor model (correlations among factors =.37, .33, .02)	11	40.7 (36) p=.27	.98	Factor 1-.76 Factor 2-.64 Factor 3-.80
Job involvement	Single-factor model	10	40.3 (30) p=.10	.97	.79
Job-related expertise	Single-factor model	4	0.1 (1) p=.81	>1.0	.84
Job slack	Single-factor model	8	22.3 (17) p=.17	.96	.76
Motivation to innovate	Two-factor model (correlation between factors = -.26)	9	28.8 (24) p=.23	.95	Factor 1-.68 Factor 2-.57
Openness to change	Three-factor model (correlation among factors =.25, -.19, -.54)	8	19.5 (15) p=.19	.98	Factor 1-.86 Factor 2-1.0 Factor 3-.83
Search resources	Single-factor model	9	32.4 (25) p=.15	.94	.66
User understanding	Single-factor model	6	9.4 (7) p=.23	.98	.85
III. Exogenous Variables					
Autonomy of job	Single-factor model	5	3.4 (3) p=.33	.99	.74
Career relevance of job	Two-factor model (correlation between factors =.50)	6	9.6 (6) p=.14	.98	Factor 1-.98 Factor 2-.86
Frequency of user contacts	Two-factor model (correlation between factors =.34)	4	---- (model is just identified with one correlated error)	----	Factor 1-.99 Factor 2-.89
Importance of current project	Equal-error congeneric single-factor model	2	---- (model is just identified)	----	.59
Personal commitment to innovation	Second-order single-factor model	9	28.0 (.22) p=.18	.97	.88
Professional orientation	Single-factor model	4	2.6 (2) p=.27	.97	.60
Support for innovation	Single-factor model	9	27.4 (24) p=.29	.99	.78
Time-horizon of professional goals	Two-factor model (correlation between factors = -.09)	4	2.0 (2) p=.37	1.0	Factor 1-.96 Factor 2-1.0

Table 4

REDUCED MODEL

PREDICTED AND ACTUAL EFFECTS ON INNOVATION

Predictor Varisble	Prediction	OLS Unstdized Coef	OLS Standardized Coef	OLS Shape, Bkpt	OLS T-Value	OLS Sgn
Number of degrees		-.726	-.007	1.9 degrees	2.87 (F)	p<.10
(Number of degrees)^2		.195	.162			
User contents-Sub.			.071	+	1.04	-----
Time in job-Cons.		.00277	.242	+	2.80	p<.01
Changes in functional area	+	.151	.237	+	2.48	p<.05
Years in work force		-.033	-.391	-	-3.50	p<.001
Professional orientation	+		.062	+	0.83	-----
Reward expectancy			-.029	-0.1	4.04 (F)	p<.05
(Reward expectancy)^2			-.158			
Autonomy			.112	+	1.39	-----
Hierarchical level		.195	.503	+	5.19	p<.001
Support for innovation			-.045	-0.7	0.30 (F)	-----
(Support for innovation)^2			-.032			
Time horizon of goals		.000649	.017	2 yr	4.82 (F)	p<.01
(Time horizon of goals)^2		-.000141	-.093			
Commitment to innovation			.120	1.4	2.02 (F)	-----
(Commitment to innovstion)^2			-.043			
Project importance	+		-.042	-	-0.60	-----
% completion of project		-.0337	.143	54%	4.55 (F)	p<.05
(% completion of project)^2		.000313	.175			

N = 154 R^2 = .453 $\overline{R}^2$ = .371

$F_{20,133}$ = 5.52 (p <. 001)

Table 5.

FULL MODEL

PREDICTED AND ACTUAL EFFECTS ON INNOVATION

Predictor Variable	Prediction	OLS Unstdized Coef	OLS Std Coef	OLS Shape, Bkpt	OLS T-Value	OLS Sgn	2SLS Unstdized Coef	2SLS Stdized Coef	2SLS Shape, Bkpt	2SLS T-Value	2SLS Sgn
Highest degree	⌞⌜	.272	.248	+	3.61	p<.001	.218	.199	+	1.78	p<.10
Time in job-Cons.	⌞⌜	.00051	.045	+	0.62	-----	.00003	.003	+	0.02	-----
Years in work force	⌞⌜	.0101	.120	+	1.53	-----	.0100	.119	+	0.76	-----
Uaer understanding	⌞⌜		.131	⌞⌜,	2.15 (F)	-----		.025	⌞⌜,	0.35 (F)	-----
(User understanding)^2			.069	-0.9				.063	-0.2		
Diversity of info-Rel.	+		.060	⌞⌝,	3.11 (F)	p<.05		.086	⌞⌝,	0.88 (F)	-----
(Diversity of info-Rel.)^2			-.148	0.2				-.120	0.4		
Job involvement	⌞⌜		-.018	-	-0.28	-----		-.147	-	-0.81	-----
Openness to change	+		.247	+	3.54	p<.001		.526	+	1.94	p<.10
Ease of implementation	+		-.166	-	-2.53	p<.05		-.349	-	-1.27	-----
Search radius	⌞⌝		.242	+	3.46	p<.001		.356	+	2.53	p<.05
Solution standards	⌞⌝		.184	+	2.83	p<.01		.208	+	2.03	p<.05
Search resources	+		.067	+	0.54	-----		.265	+	0.49	-----
Implementation resources	+		-.267	-	-2.17	p<.05		-.571	-	-0.98	-----
Sponsorship resources	+		.175	+	2.31	p<.05		.500	+	1.35	-----
Job slack	⌞⌝		-.132	-	-2.06	p<.05		-.062	-	-0.60	-----
		N = 195	R^2 = .351		$\bar{R}^2$ = .293		N = 166				
		$F_{16,178}$ = 6.02 (p<.001)									
		σ_{INNOV} = .984	SE_{est} = .827				σ_{INNOV} = .930	SE_{est} = .922			

Table 6.

SUMMARY OF RESULTS FOR THE FULL MODEL

		OLS					2SLS	
Equation	# of predic	F-stat	(df)	Sign level	R^2	SE_{est}	SE_{est}	# sign predictors
Innovation	14	6.02	(16,178)	<.001	.293	.827	.922	4
User understanding	4	8.48	(5,205)	<.001	.151	.938	.920	3
Diversity of information sources	5	2.57	(5,190)	<.05	.975	.962	.962	1
Job involvement	5	8.15	(6,183)	<.001	.185	.890	.923	3
Openness to change	6	4.30	(7,183)	<.001	.108	.954	.970	1
Acceptance for new ideas	6	2.99	(8,182)	<.01	.077	.985	.998	2
Abstract/ concrete thinking	4	8.68	(6,215)	<.001	.173	.907	---- (OLS)*	1
Solution aspiration level	3	7.22	(3,238)	<.001	.072	.964	---- (OLS)*	1
Search resources	5	2.51	(6,194)	<.05	.043	.987	1.005	1
Implementation resources	8	2.00	(9,212)	<.05	.039	1.007	1.017	2
Sponsorship resources	8	4.77	(10,211)	<.001	.146	.928	.883	1
Job slack	6	4.28	(7,184)	<.001	.107	.945	---- (OLS)*	4

*These equations are fully recursive blocks of the overall model and thus are consistently estimated using OLS.

Table 7.

INDIVIDUAL-LEVEL INNOVATION MODEL

SIMULTANEOUS EQUATION SYSTEM

$$(1)\quad INNOV = \beta_{11}JREXP + \beta_{12}JREXP^2 + \beta_{13}USERUN + \beta_{14}USERUN^2 + \beta_{15}DIV + \beta_{16}JOBINV + \beta_{17}JOBINV^2 + \beta_{18}OPEN + \beta_{19}MOTINN + \beta_{1,10}MOTINN^2 + \beta_{1,11}SCHRES + \beta_{1,12}IMPRES + \beta_{1,13}JOBSLK + \beta_{1,14}JOBSLK^2 + \tilde{u}_1$$

$$(2)\quad JREXP = \beta_{21}JOBINV + \beta_{22}EDUC + \beta_{23}TIJ + \beta_{24}TIJ^2 + \beta_{25}YRCO + \beta_{26}YRCO^2 + \tilde{u}_2$$

$$(3)\quad USERUN = \beta_{31}DIV + \beta_{32}FUC + \beta_{33}TIJ + \beta_{34}TIJ^2 + \beta_{35}BRED + \tilde{u}_3$$

$$(4)\quad DIV = \beta_{41}INNOV + \beta_{42}TIJ + \beta_{43}BRED + \beta_{44}YRWF + \beta_{45}PROFOR + \tilde{u}_4$$

$$(5)\quad JOBINV = \beta_{51}INNOV + \beta_{52}TIJ + \beta_{53}CREL + \beta_{54}PROFOR + \beta_{55}AUTNMY + \tilde{u}_5$$

$$(6)\quad OPEN = \beta_{61}INNOV + \beta_{62}INNOV^2 + \beta_{63}JOBINV + \beta_{64}TIJ + \beta_{65}TIJ^2 + \beta_{66}YRWF + \beta_{67}YRWF^2 + \beta_{68}AUTNMY + \beta_{69}HIER + \tilde{u}_6$$

$$(7)\quad MOTINN = \beta_{71}INNSUP + \beta_{72}THORZN + \beta_{73}PCI + \tilde{u}_7$$

$$(8)\quad SCHRES = \beta_{81}INNOV + \beta_{82}EDUC + \beta_{83}TIJ + \beta_{84}TIJ^2 + \beta_{86}HIER + \beta_{87}HIER^2 + \tilde{u}_8$$

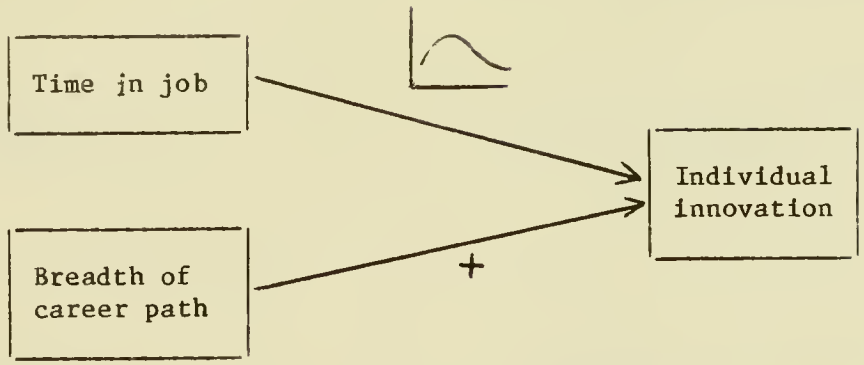
$$(9)\quad IMPRES = \beta_{91}INNOV + \beta_{92}JREXP + \beta_{93}TIJ + \beta_{94}BRED + \beta_{95}YRWF + \beta_{96}YRCO + \beta_{97}HIER + \beta_{98}IMPPRJ + \tilde{u}_9$$

$$(10)\quad JOBSLK = \beta_{10,1}TIJ + \beta_{10,2}AUTNMY + \beta_{10,3}HIER + \beta_{10,4}HIER^2 + \beta_{10,5}PCI + \beta_{10,6}PDEAD + \beta_{10,7}IMPPRJ + \tilde{u}_{10}$$

Note: All variables are assumed to be expressed in deviations from their means.

Figure 1.

Predicted Effects of Mobility Variables on Individual Innovation



. . . controlling for:

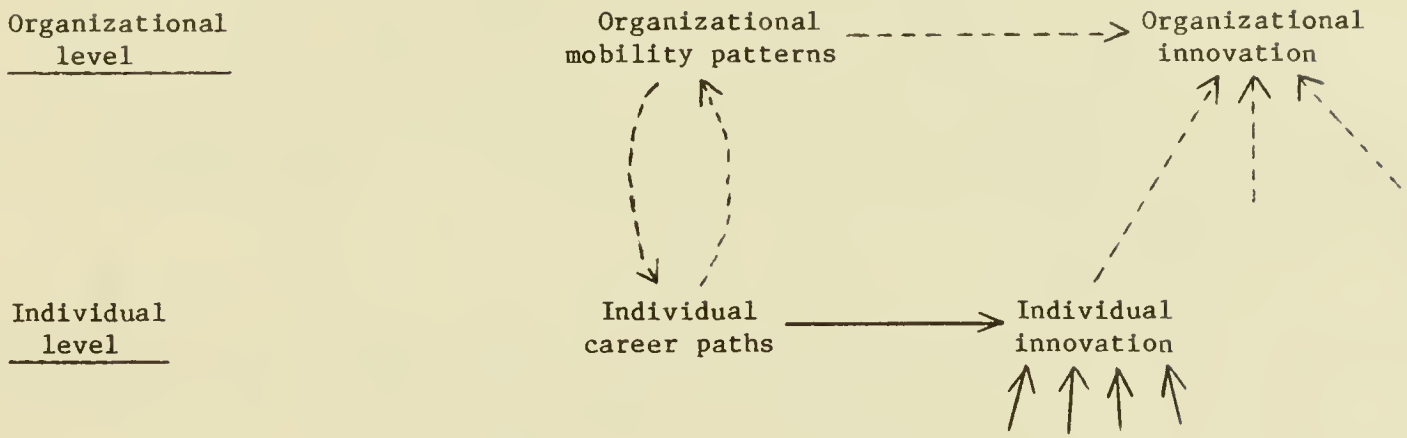
Level of education
Professionalism
Years in company
Personal commitment to innovation
Rank in hierarchy

Project-team factors
Relevance of job to career goals
Time-horizon of professional goals
Manager's support for innovation
Organizational factors

Figure 2.

Mobility & Innovation

Summary of Cross-Level Relationships



⟶ Effects tested in this study

⇢ Effects assumed for this study

Figure 3.

INNOVATION MEASUREMENT MODEL

STANDARDIZED COEFFICIENTS

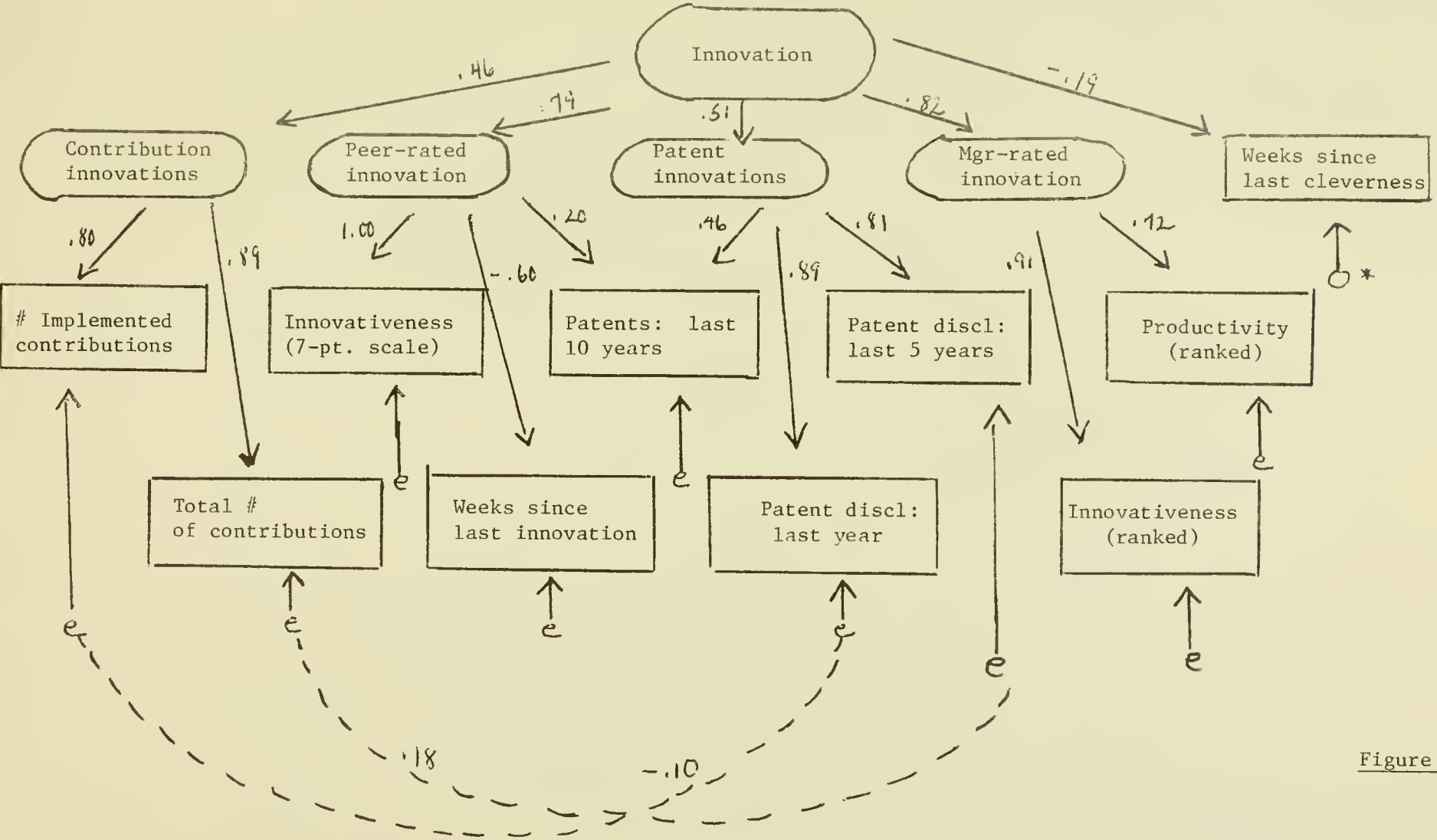


Figure 4

*constrained to equal 0.0

EFFECTS OF TIME IN JOB IN THE FULL MODEL

STANDARDIZED COEFFICIENTS

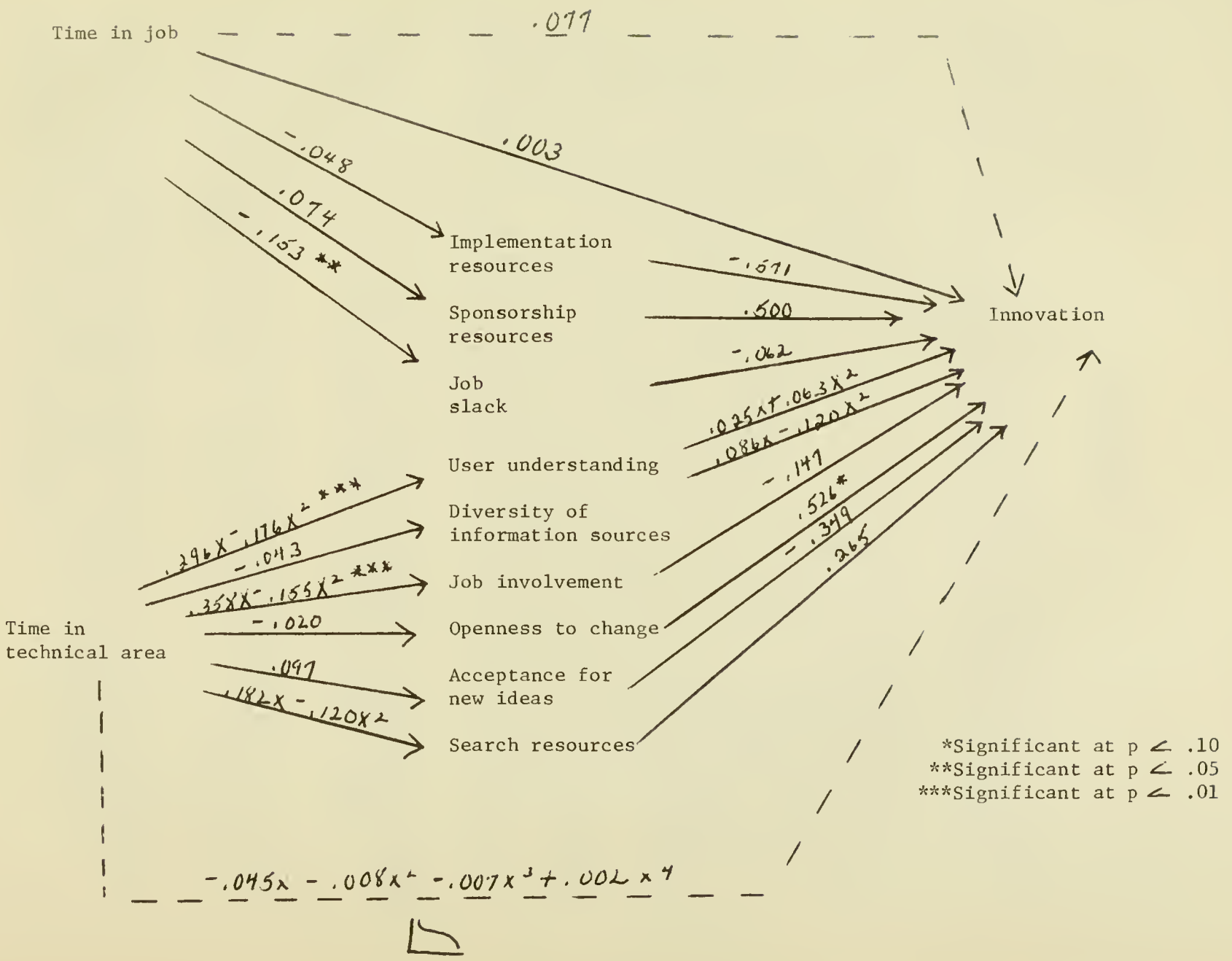


Figure 5

FOOTNOTES

1 Using the same curve-fitting technique, the government workers in Katz's (1978) study averaged 90 months or over 7 years in their jobs. Goodness-of-fit R^2s for all of these estimates were above .8 and most were above .9.

2 In contrast to the four studies which support the idea of an optimal mobility rate among projects for scientists and engineers, Stankiewicz (1979) found that productivity increased linearly with project-team age. In his study, however, project-team age was defined as the number of years since the team had been formed, rather than the average tenure of its current members. Most theories would predict a weaker relationship between this definition of project team age and productivity (Katz, 1982). Unfortunately, the data in all these studies are cross-sectional rather than longitudinal, raising questions about alternative causal explanations for the finding. For example, individual scientists and engineers might choose (or be selected for) projects of a certain duration based on their abilities (selection bias). Alternatively, they might leave projects at tenure points that are related to their abilities (retention bias). It is easy to imagine less capable scientists being allowed to remain assigned to low priority, low productivity projects, while their more respected colleagues are pulled along continually into new, more challenging ones.

3 From a different point of view, this research strategy could be considered an example of "internal analysis" (Lipset, Trow, and Coleman, 1964). Differences among individuals in a single organization are being used to infer relationships across organizations.

4 Some researchers have objected to a good portion of organizational research on the grounds that these issues were not dealt with adequately (Webb and Weick, 1979; Bagozzi and Phillips, 1982).

5 Of course, monomethod measurement modeling does not reveal which (if either) of these two factors is related to innovation in the context of the full model. In fact, as the structural model results shown below reveal, both of these factors are important to innovation, despite the fact that they are negatively correlated in the sample.

6 The incremental fit index is a practical goodness-of-fit measure that indicates the improvement in fit of the hypothesized model compared to a null model hypothesizing independent measures (Bentler and Bonett, 1980).

7 For time in job, hypotheses 1c, 1d, 1e, 1f, and 1g were counted as confirmed directionally. Hypothesis 1a was discounted since job-related expertise was removed from the full model. For career breadth, hypotheses 2a and 2b were counted as confirmed directionally.

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